International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 5, Number 2, Year 2025
DOI: https://doi.org/10.62051/ijcsit.v5n2.01
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Research on Land Cloud Detection Algorithm Based on AGRI of Fengyun-4B Satellite

Chen Zhang

Henan Polytechnic University, Jiaozuo 454003, China
chen.zhang.work@foxmail.com

ABSTRACT

Clouds are an important component of weather and climate change and have a significant impact on ecology, weather forecasting and aviation safety. Cloud detection is a preprocessing step in many satellite image processing and remote sensing inversion. Clouds not only cover the subsurface, but also absorb and scatter solar radiation, which affects the remote sensing analysis and study of the surface and reduces the utilization of data. Accurate detection of cloud-covered areas in satellite images can effectively reduce the interference of cloud cover on remote sensing data application. The Fengyun-4B Satellite is the latest generation of geostationary meteorological satellites in China, with significant performance advantages. In this paper, a land cloud detection algorithm for AGRI sensors is constructed based on the existing cloud detection algorithm using the AGRI full disk data of Fengyun 4B Satellite. Through the analysis of cloud detection product quality, the algorithm threshold is optimized to significantly improve the accuracy of cloud detection. The experimental results show that the algorithm has good overall cloud detection performance in full disk imagery, especially in the thick cloud region, but there are some misclassifications in the high brightness surface region such as the Tibetan Plateau. This study expands the application scenarios of domestic geostationary meteorological satellites, and provides new technical support for meteorological monitoring and remote sensing applications.

KEYWORDS

Fengyun-4; FY-4B; AGRI; MODIS; Cloud Detection.

1. INTRODUCTION

Clouds are the most important component of weather and climate change processes and are also important players in regulating the energy balance of the Earth's atmospheric system. Typically, clouds change the energy balance of the Earth's atmosphere by reflecting incoming solar shortwave radiation, which cools the Earth's atmosphere, and by absorbing longwave radiation emitted upward from the Earth's surface, which warms the Earth's atmosphere[1,2]. Cloud changes also play an important role in environmental ecology, daily weather forecasting, and aviation safety[3]. Clouds also obscure the area where remote sensing images are taken, affecting the application of remote sensing satellite data. Due to the cloud cover on the ground, a large amount of available information in the satellite image will be lost, and even adversely affect various applications such as atmospheric correction, parameter inversion, image alignment, and so on. Therefore, it is of great significance for the application of remote sensing satellite image data to accurately detect the cloud coverage area in satellite images[4].

Due to the uneven distribution and limitations of instrumentation, ground-based observation has a relatively large number of interfering factors in the observation area, which can cause large errors in the observation results, and ground-based observation cannot observe the continuous development of clouds in a large area. Compared with ground observation, satellite remote sensing observation can realize full-coverage observation of the Earth, and its imaging instruments carried on satellites have higher spatial and temporal resolution, which can realize continuous observation of large spatial scales and long time sequences, and due to the strong spatial and temporal variation of cloud parameters, satellite remote sensing has become one of the most important means to study cloud detection, cloud characteristics and a series of cloud inversion work[3].

In recent years, the research on cloud detection algorithms has made significant progress, mainly including threshold-based methods, machine learning-based methods and deep learning-based methods. Among them, the threshold-based methods are widely used because of their simplicity and efficiency.Ackerman et al. proposed a cloud mask algorithm for MODIS images, which dynamically adjusts the threshold according to different Earth's subsurface (snowy mountains, deserts, cities, wasteland, etc.) to achieve the ideal detection effect, which does not require a large amount of data, and has a simple and efficient processing[5].Zhu et al. also proposed a Landsat-based cloud detection algorithm (Fmask), which is based on the physical properties of clouds, identifies potential cloud pixels by calculating the spectral reflectance and brightness temperature of the surface atmosphere, and predicts the remaining cloud shadows using the Flood-FillTransformation[6].

Machine learning based methods are used to recognize clouds and mask extraction in remote sensing images by extracting multiple features (e.g., spectral features, texture features, etc.) and classifying them using algorithms such as Support Vector Machines (SVMs), Random Forests, etc. GomisCebolla et al. used different types of machine learning methods to investigate the impact of cloud detection accuracy for the complex climatic environment in the tropical Amazon region [7].Wang et al. used a random forest approach to train a passive spectral imager to combine with active radar observations for cloud detection, which further identifies the cloud phase state[8].

Deep learning-based methods automatically extract image features by constructing complex neural network models with high detection accuracy and generalization ability.Matco-Garcial used convolutional neural network (CNN) algorithms with different architectures to conduct cloud detection experiments for Proba-V multispectral images and compared the results with traditional thresholding methods as well as multi-feature extraction and supervised classification-based The results are compared with traditional thresholding methods and machine learning based on multi-feature extraction and supervised classification, and the results show that the algorithm has higher accuracy compared to traditional methods. Zhan et al. proposed a convolutional neural network based on a multilevel feature fusion strategy to learn deep patterns of cloud and snow detection from multispectral satellite images, integrating both low-level spatial feature information and high-level semantic feature information[9].

The DT (Dark Target) cloud mask algorithm of MODIS, as a cloud detection method based on multispectral thresholding, uses preset thresholds to identify clouds by comprehensively analyzing the features such as reflectance and bright temperature in multiple spectral bands, which has the advantages of high accuracy, adaptability and multi-temporal phase data support, and it is especially excellent in the detection of thin and broken clouds. At present, there are relatively few studies on cloud detection using geostationary meteorological satellites both at home and abroad, and the Fengyun 4B star, as the latest generation of China's geostationary meteorological satellites, has reached the world's leading level in terms of its performance, with extremely high spectral and temporal resolution. In view of the successful experience of MODIS DT cloud detection algorithm, this paper will draw on its multi-spectral threshold analysis and multi-temporal phase data comparison method, combined with the high spatial and temporal resolution data of Fengyun 4B AGRI sensor, to construct a land cloud detection algorithm for AGRI sensor, with a view to further enhance the effectiveness of the application of Fengyun 4B star in the field of cloud detection.

2. DATA SOURCE

The Fengyun-4B (FY-4B) is the first operational satellite of China's second-generation geostationary meteorological satellite series. It was successfully launched at 00:17 on June 3, 2021, from the Xichang Satellite Launch Center and is positioned at 133°E. The Advanced Geostationary Radiation Imager (AGRI) is one of the main payloads on FY-4B, featuring 15 spectral bands covering the wavelength range from 0.47 to 13.3 μm, spanning from visible light to infrared channels. The spatial resolution of AGRI varies across different bands, ranging from 500 meters to 4 kilometers. AGRI is capable of conducting full-disk observations every 15 minutes, completing 95 imaging cycles per day under normal conditions [10,11]. The FY-4B AGRI Level 1b (L1b) data products include observational data and geometric location data at resolutions of 500 meters, 1 kilometer, 2 kilometers, and 4 kilometers, stored in the HDF5 format. These data can be downloaded from the Fengyun Satellite Remote Sensing Data Service Network (https://satellite.nsmc.org.cn/). This study utilizes the 4-kilometer resolution AGRI observational and geometric location data for cloud detection algorithm research.

3. RESEARCH METHODS

3.1. Radiation Conversion

Before quantitative application, the extracted data need to be radiometrically calibrated to calculate reflectance ρ_λ and Top-of-Atmosphere ρ_{TOA}. The dataset NOMChannel 01~15 are the DN(Digital Number) values of the 4km channels (bands1~15), respectively, and CALIBRATION_COEF (SCALE+OFFSET) provides the slope and intercept for converting to reflectance, and Eq. (1) is used for the calibration calculations to obtain the reflectance ρ_λ and Top-of-Atmosphere ρ_{TOA}:

$$\begin{cases} \rho_\lambda = SCALE * DN + OFFSET \\ \rho_{TOA} = \dfrac{\rho_\lambda d^2}{\cos\theta} \end{cases} \tag{1}$$

where d is the Sun-Earth distance ratio, which can be obtained from the global file attributes, and θ is the solar zenith angle, which can be obtained from the corresponding GEO file.

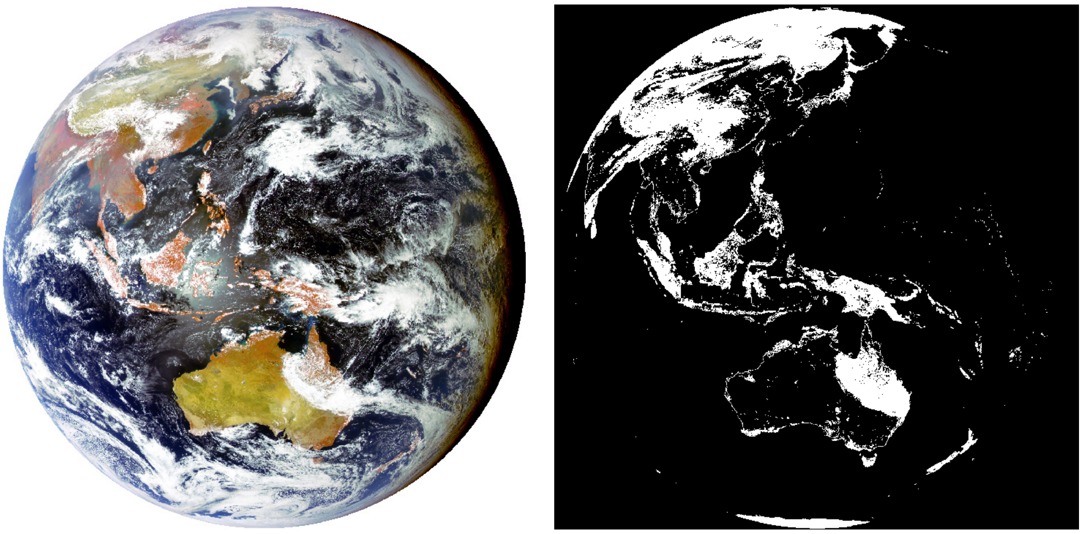
3.2. Cloud Detection Algorithm

The basic principle of cloud detection using satellite remote sensing images is based on the spectral characteristics of clouds, which have obvious spectral differences with land objects in the visible and near-infrared wavelength bands, which are reflected in the remote sensing images as different apparent albedo and radiant brightness values, and the clouds generally have higher albedo and lower brightness temperature. In this paper, we refer to the cloud mask part of the MODIS Dark Target algorithm for cloud detection of land image elements [12–14]. MODIS and AGRI belong to different types of sensors, MODIS is a polar-orbiting satellite sensor while AGRI is a geostationary orbiting satellite sensor, and their observation methods are different. Nonetheless, the AGRI sensor has a similar band design to MODIS, therefore, in this paper, the threshold of the cloud mask is adjusted to ensure that the cloud scene can be accurately recognized. In this study, we utilize the apparent reflectance and spatial variability tests in the visible blue (0.47μm) band and the near-infrared (1.38μm) band for cloud detection. Among them, the near-infrared (1.38μm) band is not sensitive to the surface and is mainly used for cirrus cloud detection. As shown in equation (2), when the apparent reflectance or standard deviation of the two bands is greater than a certain threshold, the image element is determined to be a cloud.

$$\begin{cases} \rho_{0.47}^{*} > 0.4 \\ std\_\rho_{0.47}^{*} > 0.0075 \text{且} mstd\_\rho_{0.47}^{*} > 0.02 \\ \rho_{1.38}^{*} > 0.075 \\ std\_\rho_{1.38}^{*} > 0.005 \end{cases} \quad (2)$$

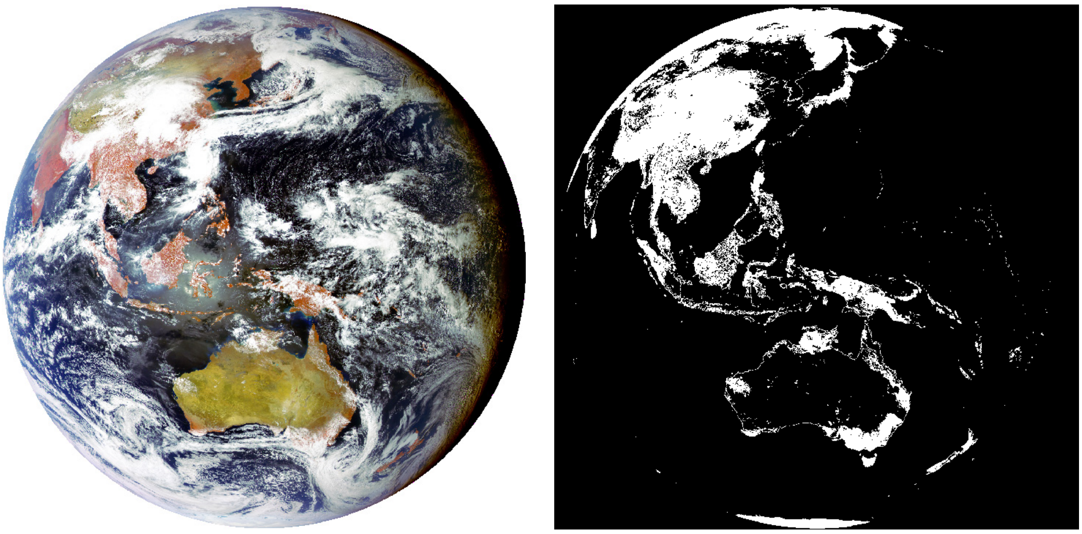
where $\rho_{0.47}^{*}$, $\rho_{1.38}^{*}$, $std\_\rho_{0.47}^{*}$ and $std\_\rho_{1.38}^{*}$ represent the apparent reflectance of the blue 0.47μm band and the near-infrared 1.38μm band, respectively, as well as the standard deviation within a 3×3 neighborhood of image elements of the two bands. $mstd\_\rho_{0.47}^{*} = std\_\rho_{0.47}^{*} \cdot \overline{\rho} \cdot \sqrt{n}$, denotes the weighted average standard deviation within a 3×3 neighborhood of image elements, where $\overline{\rho}$ denotes the average of 9 image elements within a 3×3 neighborhood, n = 9 (3×3 image elements).

4. ANALYSIS OF RESULTS



(a) AGRI false color composite image (b) Cloud detection image

Fig 1. AGRI false-color full-disk image with cloud detection on March 10, 2023



(a) AGRI false color composite image (b) Cloud detection image

Fig 2. AGRI false-color full-disk image with cloud detection on October 5, 2023

In this paper, two full-disk images of two scenes observed by the Fengyun 4B (FY-4B) AGRI sensor in 2023 are selected for cloud detection, and the effect of cloud detection is analyzed by comparing them with the false-color images. Figures 1 and 2 show the false-color images taken by the FY-4B AGRI sensor at 5:00 UTC on March 10, 2023 and 4:45 UTC on October 5, 2023, respectively, and their corresponding cloud detection results. Through visual comparison analysis, it is found that the cloud detection algorithm proposed in this paper can effectively identify cloud pixels on land, and the distribution of cloud pixels shows good consistency with the false-color images, especially in the detection of thick clouds. However, it can be clearly seen that the cloud detection effect in the Tibetan Plateau region is relatively poor, and there are more clear-sky pixels that are misclassified as clouds. This may be due to the fact that the subsurface of the Tibetan Plateau region is a bright surface with reflectivity characteristics similar to those of clouds, and thus misclassified as clouds by the algorithm. In addition, the complex topography and climatic conditions of the Tibetan Plateau also increase the difficulty of cloud detection.

5. CONCLUSION AND DISCUSSION

In this paper, a terrestrial cloud detection algorithm is proposed based on the AGRI sensor data of the Fengyun-4B (FY-4B) Satellite. The algorithm analyzes the apparent reflectance and spatial variability in the visible blue (0.47μm) and near-infrared (1.38μm) bands and combines them with threshold conditions for cloud identification. The full-disk images of the two views in 2023 are selected for analysis, and the results show that the algorithm performs well in thick cloud detection, and the comparison with the false-color images shows high consistency in cloud pixel distribution. However, in high-brightness surface regions such as the Tibetan Plateau, the surface reflectivity is similar to that of clouds, resulting in some clear-sky image elements being misclassified as clouds, and the detection effect is poor. Future research will optimize the algorithm in the following three aspects: first, introducing multi-temporal data comparison, distinguishing dynamic clouds from static highlighted surfaces by analyzing the changing characteristics of clouds in different time-phase images; second, combining deep learning techniques, such as convolutional neural networks (CNNs), to automatically extract image features, reducing the subjectivity of artificially set thresholds, and improving the algorithm's generalization ability; and third, setting a region-adaptive threshold. Optimize the threshold setting for different surface types to reduce the misjudgment rate. Through these improvements, the algorithm will enhance the detection accuracy and adaptability under different surface and cloud conditions, providing more accurate cloud information support for meteorological forecasting, ecological environment monitoring and remote sensing data applications.

REFERENCES

[1] Dessler A E. A determination of the cloud feedback from climate variations over the past decade[J]. Science, 2010, 330(6010): 1523-1527.

[2] Baker M B, Peter T. Small-scale cloud processes and climate[J]. Nature, 2008, 451(7176): 299-300.

[3] Yang, Shu. Cloud Detection Algorithm for AHI imager onboard Himawari-8 Geostationary Satellite based on Machine Learning [D]. Nanjing: Nanjing University of Information Science & Technology, 2022.

[4] Yang, Chenyang. Cloud Detection Algorithm Research and Prototype System Design Based on FY4 Data [D]. Nanjing: Nanjing University of Information Science & Technology, 2021.

[5] Ackerman S A, Strabala K I, Menzel W P, et al. Discriminating clear sky from clouds with MODIS[J]. Journal of Geophysical Research: Atmospheres, 1998, 103(D24): 32141-32157.

[6] Zhu Z, Woodcock C E. Object-based cloud and cloud shadow detection in Landsat imagery[J]. Remote Sensing of Environment, 2012, 118: 83-94.

[7] Gomis-Cebolla J, Jimenez J C, Sobrino J A. MODIS probabilistic cloud masking over the amazonian evergreen tropical forests: a comparison of machine learning-based methods[J]. International Journal of Remote Sensing, 2020, 41(1): 185-210.

[8] Wang C, Platnick S, Meyer K, et al. A machine-learning-based cloud detection and thermodynamic-phase classification algorithm using passive spectral observations[J]. Atmospheric Measurement Techniques, 2020, 13(5): 2257-2277.

[9] Zhan Y, Wang J, Shi J, et al. Distinguishing Cloud and Snow in Satellite Images via Deep Convolutional Network[J]. IEEE Geoscience and Remote Sensing Letters, 2017, 14(10): 1785-1789.

[10] Si Y, Gao L, Chen L, et al. An Adaptive Dark-Target Algorithm for Retrieving Land AOD Applied to FY-4B/AGRI Data[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2024, 17: 14035-14049.

[11] Zhou D, Wang Q, Li S, et al. Preliminary Retrieval and Validation of Aerosol Optical Depths from FY-4B Advanced Geostationary Radiation Imager Images[J]. Remote Sensing, 2024, 16(2): 372.

[12] Levy R C, Mattoo S, Munchak L A, et al. The Collection 6 MODIS aerosol products over land and ocean[J]. Atmospheric Measurement Techniques, 2013, 6(11): 2989-3034.

[13] YANG L, HU X, WANG H, et al. Preliminary test of quantitative capability in aerosol retrieval over land from MERSI-II onboard FY-3D[J]. National Remote Sensing Bulletin, 2022, 26(5): 923-940.

[14] Yang L, Ji W, Pei X, et al. Global evaluation of Fengyun-3 MERSI dark target aerosol retrievals over land[J]. International Journal of Digital Earth, 2024, 17(1): 1-24.